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RESEARCH ARTICLE

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Influence of landscape and hydrological factors on stream–air temperature relationships at regional scale

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Abstract

Identifying the main controlling factors of the stream temperature (T_w) variability is important to target streams sensitive to climate and other drivers of change. The thermal sensitivity (TS), based on relationship between air temperature (T_a) and T_w , of a given stream can be used for quantifying the streams sensitivity to future climate change. This study aims to compare TS for a wide range of temperate streams located within a large French catchment (110,000 km²) using 4 years of hourly data (2008–2012) and to cluster stations sharing similar thermal variabilities and thereby identify environmental key drivers that modify TS at the regional scale. Two successive classifications were carried out: (a) first based on T_a – T_w relationship metrics including TS and (b) second to establish a link between a selection of environmental variables and clusters of stations. Based on weekly T_a – T_w relationships, the first classification identified four thermal regimes with differing annual T_w in terms of magnitude and amplitudes in comparison with T_a . The second classification, based on classification and regression tree method, succeeded to link each thermal regime to different environmental controlling factors. Streams influenced by both groundwater inflows and shading are the most moderated with the lowest TS and an annual amplitude of T_w around half of the annual amplitude of T_a . Inversely, stations located on large streams with a high distance from source and not (or slightly) influenced by groundwater inflows nor shading showed the highest TS , and so, they are very climate sensitive. These findings have implications for guiding river basin managers and other stakeholders in implementing thermal moderation measures in the context of a warming climate and global change.

KEYWORDS

CART method, classification, regional scale, stream temperature, thermal sensitivity

1 | INTRODUCTION

Water temperature (T_w) is a fundamental water quality parameter that controls aquatic community structure and affects ecological processes in rivers and streams (Caissie, 2006; Comte, Buisson, Daufresne, &

Grenouillet, 2013; Jonsson & Jonsson, 2009; Webb, Hannah, Moore, Brown, & Nobilis, 2008). The impacts of global change on hydro-systems are potentially numerous and result from changes in extreme precipitation frequency and increased air temperature (T_a), evaporation, and dry periods (e.g., Garner, Hannah, & Watts, 2017; Watts

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et al., 2015). The rise of T_a is expected resulting in warmer stream T_w (Garner, Hannah, Sadler, & Orr, 2014; Hannah & Garner, 2015; Mohseni & Stefan, 1999; van Vliet et al., 2013), which could be exacerbated by the reducing of summer stream flows especially in temperate climate (Isaak et al., 2010; van Vliet et al., 2013). In France, several studies have already highlighted an increase in T_w across various rivers (Bustillo, Moatar, Ducharne, Thiéry, & Poirel, 2014; Jackson, Fryer, Hannah, & Malcolm, 2017; Jackson, Fryer, Hannah, Millar, & Malcolm, 2018; Jackson, Hannah, Fryer, Millar, & Malcolm, 2017; Moatar & Gailhard, 2006). There is therefore a growing interest in understanding the spatio-temporal variability of river thermal regime given the likely effects of climate change (increase of both the T_a and the evapotranspiration, shift in river flow regimes and of groundwater inflows, etc.; Webb et al., 2008; Moatar et al., 2010). The goal is to develop opportunities for mitigation and adaptive management of river systems (Boisneau, Moatar, Bodin, & Boisneau, 2008; Hrachowitz, Soulsby, Imholt, Malcolm, & Tetzlaff, 2010; Jackson, Malcolm, & Hannah, 2015; Kurylyk, MacQuarrie, Linnansaari, Cunjak, & Curry, 2015).

The T_w variability, described by metrics of flow magnitude, frequency, duration, timing, and rate of change, on various timescales (Jones & Schmidt, 2018), is influenced by complex processes related to atmospheric, hydrogeological, geomorphic, and landscape characteristics and anthropogenic pressures, which could interact at multiple spatial scales (Caissie, 2006; Hannah & Garner, 2015). Numerous studies have highlighted the importance of riparian forest and groundwater inflows in moderating T_w variability (Dugdale, Malcolm, Kantola, & Hannah, 2018; Garner, Malcolm, Sadler, & Hannah, 2017; Kelleher et al., 2012; Lalot et al., 2015; Loicq, Moatar, Jullian, Dugdale, & Hannah, 2018). Identifying the main controlling factors of T_w variability remains an important task to target streams sensitive to climate change and to develop mitigation action to preserve aquatic ecosystems (Jackson et al., 2018).

Classification and regression tree (CART) of hydrological and landscape-dependent variables are informative and revealing methods to answer explore patterns without introducing an a priori structure of the link between explanatory variables and metrics describing T_w variability (Arismendi, Johnson, Dunham, & Haggerty, 2013; Casado, Hannah, Peiry, & Campo, 2013; Chu, Jones, & Allin, 2009).

Some studies, in various parts of the world, considered explicitly and empirically the role of a limited number of basin properties on T_w (e.g., Garner et al., 2014; Hrachowitz et al., 2010; Jackson et al., 2015; Faye L. Jackson, Fryer, et al., 2017; Faye L. Jackson et al., 2018; Jackson, Hannah, et al., 2017 in the UK; Isaak & Hubert, 2001; Isaak et al., 2010; Nelitz, MacIsaac, & Peterman, 2007, in North America). Analyses in most of these studies are carried out on a site-by-site basis, which limits the extent to which broad patterns can be inferred (Laizé, Bruna Meredith, Dunbar, & Hannah, 2017). Some regional-scale studies have used spatial thermal regime classification based on a large set of catchment properties (Chu et al., 2009; Laizé et al., 2017; Maheu, Poff, & St-Hilaire, 2016; Rivers-Moore, Dallas, & Morris, 2013; Tague, Farrell, Grant, Lewis, & Rey, 2007). These studies succeeded in identifying key drivers that influence the thermal regime

of streams at the regional scale. Most of these studies use on metrics summarizing the warmest aspects of the T_w regime to examine the threats to cold-water species under climate change.

Several researchers analyse the relationship between T_w and T_a , with T_a taken as a surrogate of the main climatic drivers (Ducharne, 2008; Garner et al., 2014). T_a is a common variable, easily measured on the field, and it is strongly correlated to solar radiation (Bustillo et al., 2014). Kelleher et al. (2012) studied the thermal sensitivity (TS) of streams to represent the relative sensitivity of T_w of a given stream to environmental change. TS is defined as the slope of the regression line between T_a and T_w , which can be linear (or logistic) and can be fitted on data averaged at different timescales (Mohseni & Stefan, 1999; O'Driscoll & DeWalle, 2006; Stefan & Preud'homme, 1993). TS summarizes the cumulative buffering effects of local landscape characteristics on stream temperatures. Although TS may evolve into the future due to the changing drivers considered above, TS computed for a specific period of record gives insight of which streams have the greatest sensitivity to climate based on contemporary conditions, which can be used as a baseline for responsiveness (Kelleher et al., 2012). However, this integrated variable cannot distinguish the cause and effect of groundwater and riparian vegetation shading on T_w variability (Chang & Psaris, 2013; Chu et al., 2009; O'Driscoll & DeWalle, 2006). Understanding the importance of these driving factors is essential to develop appropriate strategies to mitigate and adapt to stream heating under anticipated climate warming.

The aim of our study is (a) to provide a comparison of thermal sensitivity (TS) across a wide range of French temperate streams, based on 4 years of hourly data (2008–2012), and (b) to identify groups of streams with similar sensitivity and so infer the environmental key factors that control TS at the regional scale. For that purpose, two successive classifications of 127 stations located in the Loire catchment (Beaufort et al., 2016) were carried out: (a) first based on T_a – T_w relationship metrics including TS and (b) second to establish a link between a selection of environmental variables and thermal regimes of stations. Finally, the relative importance of environmental variables on the TS of streams is investigated, and the implication for river management and river restoration is discussed.

2 | MATERIAL AND METHODS

2.1 | Sites and temperature data

2.1.1 | Basin description

The Loire basin (Figure 1) comprises a hydrographical network of 88,000 km and drains a catchment area of 117,000 km². It is characterized by varying climates between the upstream and the downstream (annual rainfall between 550 and 2,100 mm/year and annual air temperature between 6°C and 12.5°C), landform (10% of the basin area >800 m; mean altitude = 300 m), and lithology (metamorphic, magmatic, and sedimentary rocks). The percentage of riparian vegetation, defined on a buffer zone of 10 m on both sides of the streams, is globally greater in the southern basin where the altitude is the highest (mean ratio of the riparian

vegetation = 75%; dark green; Figure 1c). Streams located in the central part of the basin, mainly composed of sedimentary rocks, benefit more from groundwater contributions (Figure 1d). The main aquifers are found in the sedimentary rocks in the centre of the basin. The Beauce formations (12,700 km²) are composed of many semipermeable aquifers (Mohseni & Stefan, 1999) with numerous groundwater inflows located at the north of the Loire basin. Some streams are very directly connected to this aquifer, and their flow depends on the level of the Beauce water table (Baratelli, Flipo, & Moatar, 2016).

2.1.2 | Field monitoring

T_w was monitored, hourly, at 127 stations managed by the French Agency for Biodiversity (<http://www.naiades.eaufrance.fr>), between July 2008 and December 2012, distributed across the Loire basin

(Figure 1b). The monitoring stations are mainly located on streams with a Strahler order between 3 and 5 (78% of stations). All monitoring stations are located on streams with low direct human influence on the flow regime, and all time series of *T_w* have been scrutinized to discard streams influenced by dam operations. The mean annual water temperatures of these stations range from 7.5°C to 15.7°C. The highest mean annual temperatures were observed on large rivers such as the Loire (Strahler Order 8) and its main tributaries, where mean annual *T_w* ranged between 14°C and 15.7°C between 2008 and 2012 (Figure 1a; Beaufort et al., 2016). Colder temperatures (<9°C) were observed in the upstream reaches of the Loire River where the altitude is above 1,000 m. The annual *T_w* at stations located on small streams (51 stations <30 km from upstream sources) did not exceed 13°C (Figure 1b). Moreover, gaps in *T_w* time series between 2008 and 2012 exist, and the proportion of missing values is about 35% on average for the 127 stations (80 stations with more than 20% of missing

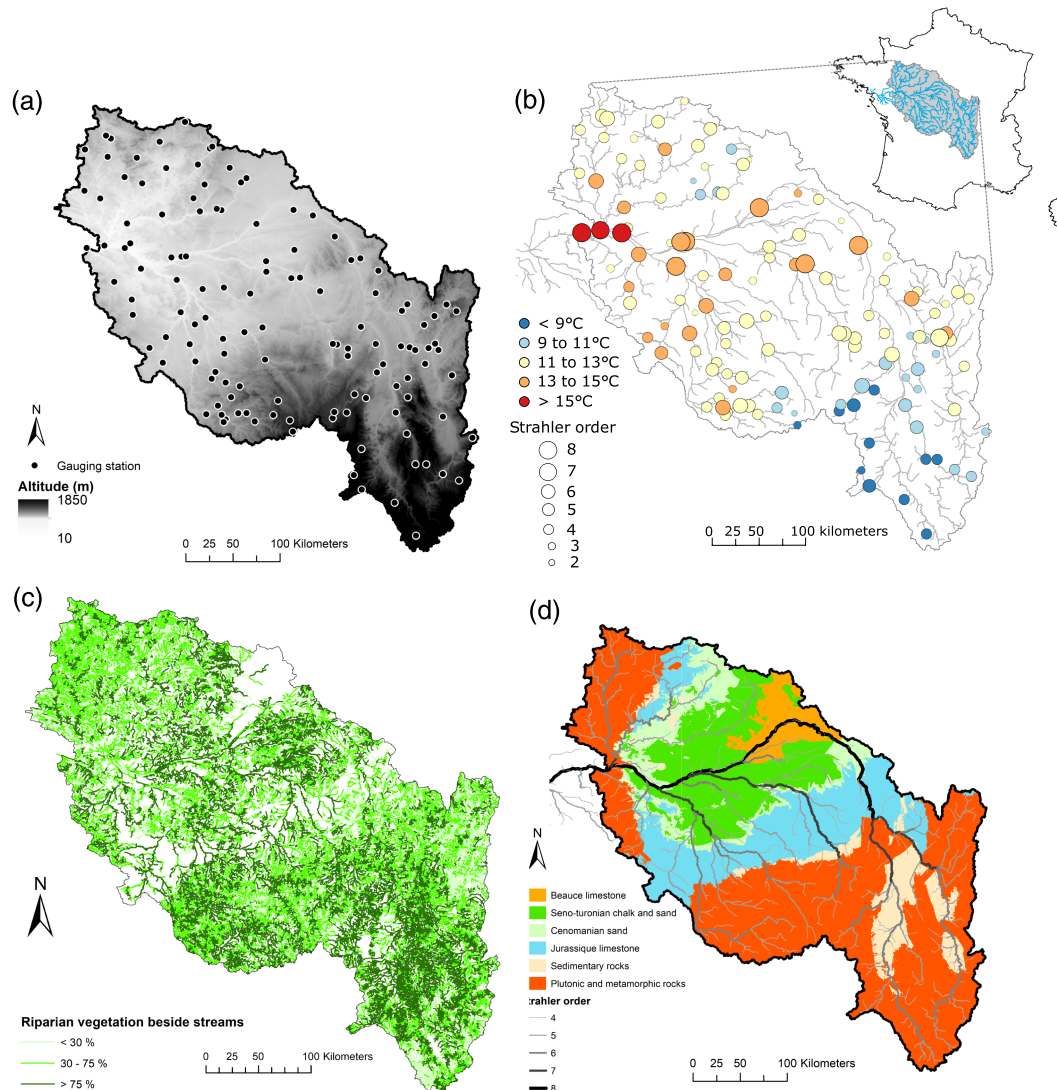


FIGURE 1 Presentation of the Loire catchment: (a) altitude and location of monitoring stations, (b) location of the 127 water temperature monitoring stations presented with the spatial distribution of mean annual stream temperatures (*T_w*), (c) vegetation cover besides streams (Valette, Piffady, Chandresis, & Souchon, 2012), and (d) main aquifer formations and basin lithology

values in time series). To limit biases in the calculation of indicators for each station, hydrological years with more than 15% of missing daily values (threshold based on previous studies (Beaufort et al., 2016; Aurélien Beaufort, Lamouroux, Pella, Datry, & Sauquet, 2018)) or with missing values during August or January are excluded from the analysis. The length of available records for the 127 stations time series varies between 1 (56 stations), 2 (29 stations), 3 (27 stations), and 4 years (15 stations).

The hourly T_a was taken from the SAFRAN (Système d'analyse fournissant des renseignements atmosphériques à la neige) reanalysis data (grid 8 km) at hourly time step between 2008 to 2012 (Quintana-Seguí et al., 2008; Vidal, Martin, Franchistéguy, Baillon, & Soubeyroux, 2010). T_a is extracted from the SAFRAN mesh (64 km²) overlapping the station. The mean annual T_a of these stations ranges from 6.4°C to 12.5°C. The coldest temperatures are observed in the mountainous part of the basin (mean annual $T_a < 10^\circ\text{C}$), whereas the warmest temperatures are observed in the west and in the sedimentary plain (mean annual $T_a > 11^\circ\text{C}$).

Both hourly T_a and T_w have been averaged over the day and over the week in the next section.

2.2 | Metrics of air–water temperature relationship

We used four metrics to characterize the relation between air and water temperature. (a) Two of these metrics, the thermal sensitivity (TS) and intercept (b), provide information on the link between weekly T_w and T_a over the year. Weekly linear regressions were selected on the basis of the best mean R^2 fitted for the 127 stations in comparison with daily or logistic regressions.

For each station, a linear regression is fitted between the weekly T_w (T_w7D) and the weekly T_a (T_a7D) and the distribution of slopes, hereafter called thermal sensitivity (TS), and intercept (b) were analysed (Equation 1; Kelleher et al., 2012; O'Driscoll & DeWalle, 2006).

$$T_w7D = T_a7D \times TS + b. \quad (1)$$

(b) Two others metrics, ΔT_{Jan} and ΔT_{Aug} , are based on the seasonal difference between monthly T_w and T_a . For all stations, the monthly T_w (MT_w) is the coldest in January and the warmest in August. To account for the relative sensitivity of T_w during extreme months, we introduced two metrics, which are the differences between the monthly T_a (MT_a) and T_w in January (ΔT_{Jan}) and in August (ΔT_{Aug}) averaged between 2012 and 2016:

$$\Delta T_{Jan} = \frac{\sum_{i=1}^{Ny} (MT_{a,Jan}(i) - MT_{w,Jan}(i))}{Ny}, \quad (2)$$

$$\Delta T_{Aug} = \frac{\sum_{i=1}^{Ny} (MT_{a,Aug}(i) - MT_{w,Aug}(i))}{Ny}, \quad (3)$$

where ΔT is the mean difference between monthly T_a (MT_a) and T_w (MT_w) calculated in January or August, $MT_{a,Jan}(i)$ and $MT_{a,Aug}(i)$ are respectively the monthly T_a in January and August of the year i , $MT_{w,Jan}(i)$ and $MT_{w,Aug}(i)$ are respectively the monthly T_w in January and August of the year i , and Ny is the number of year where monthly T_a and T_w are both available ($1 \leq Ny \leq 4$, see Section 2.1).

2.3 | Explanatory variables

A set of eight explanatory variables was selected to explain the observed spatial pattern in TS and identify main drivers of thermal streams moderation. The variable selection was based on the most pertinent variables identified in literature and on the results of a principal component analysis (not presented here) to minimize dependency between variables.

The distance from the source (D in km) and the elevation (E in m) are determined at the location of each monitoring station. The slope of the river reach (S in m m⁻¹) where the station is located is determined with BD ALTI[®] 25-m resolution DTM dataset (IGN Paris, France). A higher S increases the flow velocity, and E influences T_w through the association with the adiabatic lapse rates of T_a and also through snow and glacier meltwater inflow, which should cool T_w at higher elevations. Streams with a high D have more time to equilibrate their T_w with T_a .

Two hydrological indicators were also introduced. (a) The base-flow index (BFI) was estimated with the method of the Institute of Hydrology (1980) between 2008 and 2012. The BFI is a measure of the proportion of the low-flow component to the total river flow with values between 0 and 1. Details on calculation can be found in Gustard, Bullock, and Dixon (1992). Low values are related to catchments with no storage capacity and also to catchments exposed to very high climate variability resulting in severe low-flow and quick run-off in response to rainfall events. High values are observed where artificial reservoirs, large aquifers, and storage in snow packs moderate the variability of daily flow. In our study, BFI is considered as a proxy of groundwater influence. The discharge Q was not monitored at T_w station, and each T_w station was coupled to the nearest gauging station (distance between both stations ranges from 10 m to 15 km). The matching is based on two criteria: (a) The gauging stations has to be located in the same or nearby streams and (b) the difference of catchment area between the location where T_w was measured and the location where Q was measured was kept to a maximum of $\pm 20\%$. The daily discharge was extracted from the French river flow monitoring network (HYDRO database, <http://www.hydro.eaufrance.fr/>). (b) The average specific discharge in August (Q_{Aug}) is calculated at each station between 2008 and 2012. The goal is to measure the capacity of the catchment to produce a flow in summer, when precipitation is low. The specific discharge is the ratio between the discharge and the corresponding catchment area (in L s⁻¹ km⁻²) and is used to standardize discharge for basin area.

Two climatic variables were determined from the Safran reanalysis data: (a) the mean summer cumulated precipitation (P in mm) and (b) the mean summer potential evapotranspiration (PET in mm) both

calculated between June 1 and September 30 of each year between 2008 and 2012 for the entire upstream area of each monitoring station. Streams with wetter basin (high *P* and low *PET*) are expected to have higher water yields and more groundwater contributions that should cool streams (Isaak et al., 2017).

One variable was determined to characterize the riparian vegetation. A shading factor (*SF*), corresponding to a coefficient of reduction of the overall incident radiation, was estimated by Valette et al. (2012). *SF* gives the averaged vegetation cover (%) derived from a buffer of 10 m of vegetation polygons on both sides of reaches from the BD TOPO® database, provided by Institut national de l'information géographique et forestière (IGN). *SF* has been calculated between 7 a.m. and 9 p.m. over the summer period between June 1 and September 30 over the period 2008–2012, when the effect of shading is at its annual seasonal maximum for the North Hemisphere. The model of Li, Jackson, and Krasieski (2012) was implemented in its simplest version, that is, considering rectangular trees, located at the edge of the bank, without overhang.

$$SF = \frac{H \times \cot \Psi \times \sin \delta}{W} \times vc, \quad (4)$$

where *H* is the tree height (assumed to be 20 m everywhere), *W* is the stream width, estimated using the ESTIMKART empirical model (Lamouroux et al., 2010), Ψ is the solar elevation angle, δ is the angle between solar azimuth and the mean azimuth (0–180°) of the river reach, and *vc* is the vegetation cover (%).

2.4 | Statistical classification and explanatory variables

2.4.1 | Thermal regimes clustering

To identify natural thermal regimes of stations sharing similar *Ta*–*Tw* relationship, an agglomerative hierarchical clustering (AHC) has been used. The AHC is based on the four metrics described above (*TS*, *b*, ΔT_{Jan} , and ΔT_{Aug}). The Euclidean distance is used to measure the dissimilarity, and clusters are found with the Ward's minimum variance method. The stability of clusters is assessed through a bootstrap approach with the R package “fpc” (Hennig, 2019), and the similarity between each new cluster set and initial cluster was assessed with the Jaccard index (Hennig, 2007; Maheu et al., 2016). The Jaccard coefficient ranges from 0 to 1, and a cluster with a coefficient larger than 0.75 can be considered as stable (Maheu et al., 2016). Each thermal regime identified is described in terms of magnitude (mean *Tw* over a month) and amplitude (differences between the maximum and minimum values of *MTw*) and compared with *MTa*.

2.4.2 | Identification of environmental drivers in thermal sensitivity

A CART is used to examine the relationship between *TS* and the set of explanatory variables described above. CART analysis (Breiman, Friedman, Stone, & Olshen, 1984) is nonparametric and non-linear and does

not introduce an a priori structure of the link between explanatory variables and the variable to be explained contrary to generalized linear models implicit assumption (Breiman et al., 1984; Ripley, 1996). CART recursively partitions observations in a matched data set, consisting of *TS* (response) and the eight explanatory variables, into progressively smaller groups (De'ath & Fabricius, 2000). Each partition is a binary split. During each recursion, splits for each explanatory variable are examined, and the split that leads to the most homogeneous subgroups with respect to the dependent variable is chosen. The interpretation of results summarized in a tree with series of logical if-then conditions (tree nodes) is very simple. We used the R package “rpart” (Version 4.1, Therneau & Atkinson, 2018) for implementing the CART model. The random forest (RF) model was used to assess the importance of explanatory variables for the prediction of *TS* and to evaluate the robustness of the classification. RF combines decision trees obtained by resampling the calibration set (Breiman, 2001), which is constituted by selecting randomly 80% of the observations (80% of 127 stations × eight explanatory variables × *TS*), and the test set consists of the remaining 20%. We used the implementation in the R package “randomForest” (Liaw & Wiener, 2002). The explanatory variable importance is given directly by the “randomForest” algorithm, which determines how much the mean square errors in prediction increases when that covariate is randomly permuted within the tree. The random selection is performed 100 times, and the explanatory variables importance for each test set was then averaged.

3 | RESULTS

3.1 | Distribution of thermal sensitivity and link with catchment size

The R^2 values for weekly *Ta* and *Tw* ranged from 0.83 to 0.98, with values greater than 0.9 at 123 of the 127 sites. *TS* ranges from 0.42 (Figure 2b) to 1.2 (Figure 2a), and *b* ranges from 0.5°C to 7.5°C. Regression lines plotted for the 127 stations showed a higher range of values of *Tw* when *Ta* is high at the regional scale (*Tw* ranges between 15°C and 30°C when *Ta* is 25°C) than when *Ta* is low (*Tw* ranges between 0°C and 7.5°C when *Ta* is 0°C; Figure 2c).

The relationship between *TS* and *b* shows a moderate negative correlation with $R^2 \approx 0.7$. Stations with the lowest *TS* (<0.6) and the highest *b* have the highest residual and seemed to follow a different pattern than other stations (Figure 3a; all the points are located above the regression line). Stations having a moderate *TS* between 0.6 and 0.9 are most often observed across the Loire River basin, and their associated *b* ranges from 1°C to 5°C. Stations with a high *TS* (>0.9) and a small *b* (<3) follow the same trend and have small residuals of the slope intercept regression. The analysis of weekly *Ta*–*Tw* relationship indicates that *TS* generally increases with stream size and the distance from source (Figure 3b). Streams with a distance from source higher than 100 km² obtain a *TS* higher than 0.7. For small and medium rivers (*D* < 100 km), the range of *TS* is large and between 0.42 and 1.

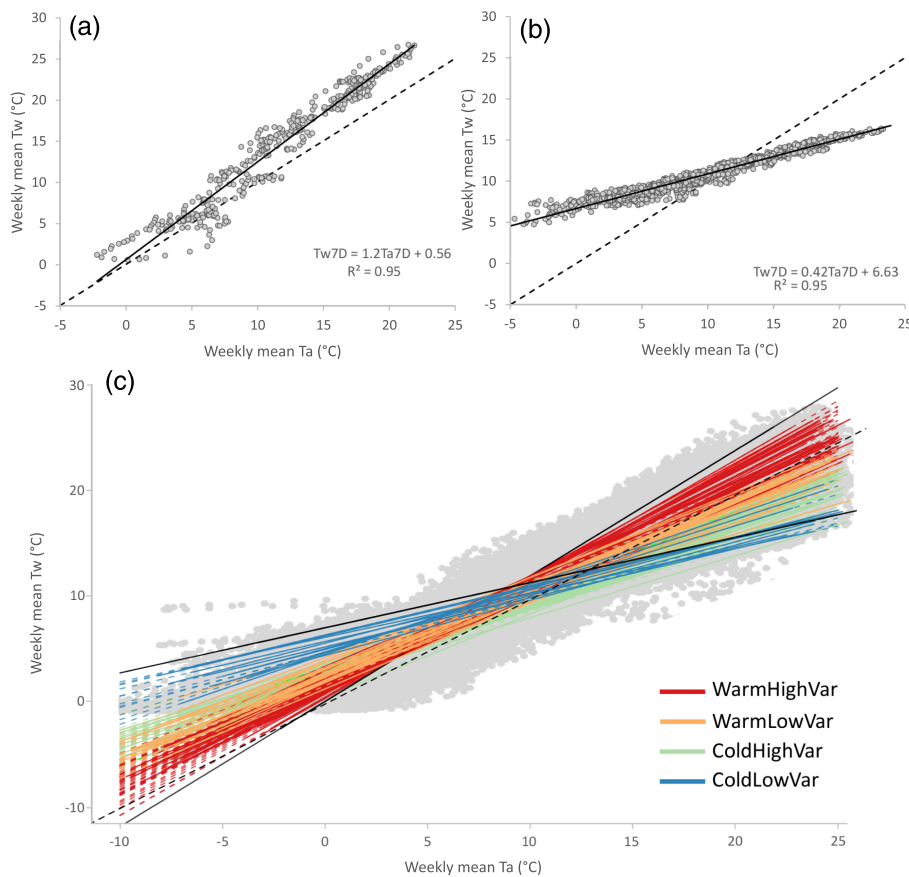


FIGURE 2 $Tw-Ta$ weekly linear regression: (a) for the station with the highest TS, (b) for the station with the lowest TS, and (c) for the 127 stations fitted on data available between 2008 and 2012. Dashed lines represent the curve $x = y$, solid lines represent the weekly linear regression curves for each station, and the black solid lines in (c) correspond to weekly linear regression curves of stations represented in (a) and (b), and grey points in (c) represents all the observations

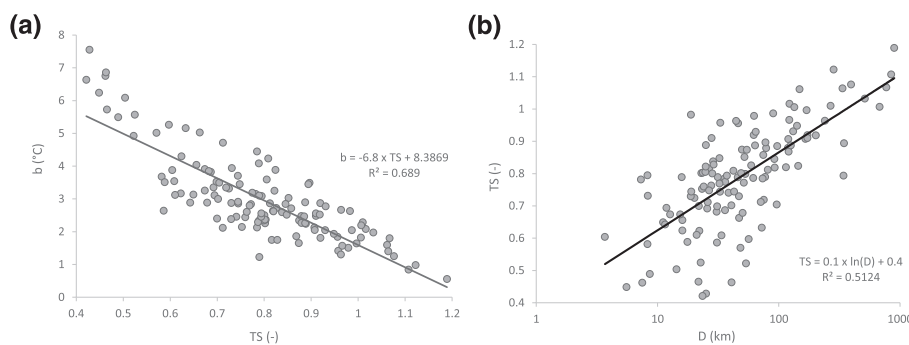


FIGURE 3 Distribution of TS: (a) relationship between b and TS of weekly $Tw-Ta$ linear regressions and (b) TS as a function of the distance from the source (D) of monitoring stations

The analysis of the spatial distribution of TS in the Loire basin shows that the stations obtaining the smallest TS ($TS < 0.5$) are located in the sedimentary plain where the main aquifer formations are located (Figure 4). The stations with the highest TS ($TS > 0.9$) are located along large rivers in the sedimentary plain and in the western side of the basin where the altitudes are the lowest and Ta the highest. Finally, stations located in the regions with the highest altitude obtain a moderate TS lower than 0.7.

3.2 | Cluster classification analysis

The AHC yielded four clusters of station corresponding to four thermal regimes:

- **WarmHighVar**—warm and high variability (47 sites—37%): stations characterized by low b ($< 3^\circ\text{C}$) and high TS (> 0.8). At these stations, MTw is higher than MTa in January and August with a median difference of 1.5°C (Table 1). These stations are those with the highest annual amplitude of MTw reaching 18°C with similar annual MTa amplitude (red area; Figure 5a,b). Their $MTws$ are the warmest during summer and exceed 21°C on average.
- **WarmLowVar**—warm and low variability (23 sites—18%): These stations are characterized by a smaller TS and a higher b (median $b = 3.5^\circ\text{C}$) than stations from WarmHighVar. MTa is less than MTw in winter with a median deviation of 3°C . In August, the MTw is very close to MTa , and ΔT_{Aug} does not exceed 1°C . They have annual MTw amplitude of 14°C and MTw smaller than 4°C in

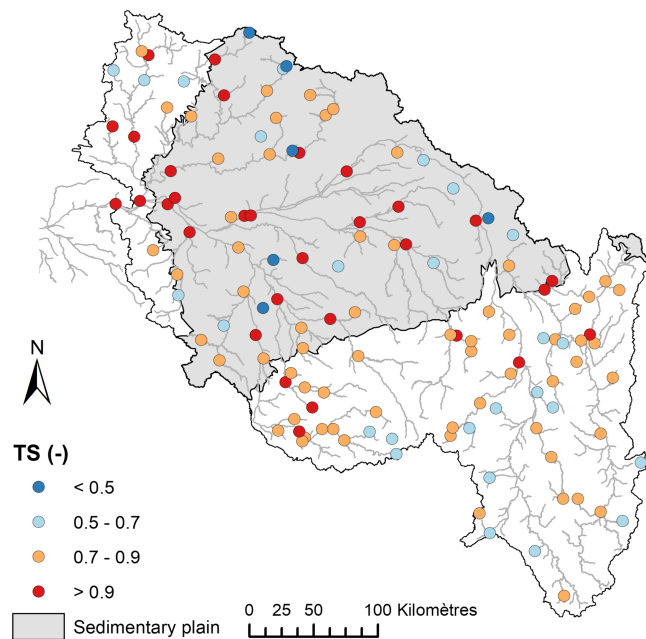


FIGURE 4 Spatial distribution of TS calculated between 2012 and 2016 on weekly T_a - T_w regressions

summer in comparison with the MTw of stations from WarmHighVar (yellow area; Figure 5a,b).

- ColdHighVar—cold and high variability (44 sites—35%): Stations have MTw higher than MTa in January by 2°C (Table 1). Inversely, in August, MTw is less than MTa by 2°C . The TS and b of stations have rather average values with medians of 0.7 and 2.9, respectively. They have annual MTw amplitude of 14°C and MTw less than 5°C in summer in comparison with the MTw of stations from WarmHighVar (green area; Figure 5a,b).
- ColdLowVar—cold and low variability (13 sites—10%): Stations demonstrate the lowest TS of each class ($TS < 0.7$) and the highest b (greater than 4.9°C). The differences between MTw and MTa are high, in comparison with other thermal regimes, whether in August ($MTa > MTw$ by 3.5°C) or in January ($MTa < MTw$ by 4°C). These

stations are those with the lowest annual MTw amplitude of 9°C , which is one half less than the amplitude of stations from WarmHighVar (blue area; Figure 5a). The MTw of stations from ColdLowVar is the lowest during summer ($MTw = 15^\circ\text{C}$) and the warmest during winter in comparison with others thermal regimes (Figure 5c).

The thermal regimes named “WarmHighVar” and “ColdLowVar” were stable clusters and had a Jaccard coefficient larger than 0.7. The thermal regimes called “WarmLowVar” and “ColdHighVar” were less stable clusters and had Jaccard coefficients of 0.55 and 0.61, respectively. The analysis of the deviation from the mean annual Tw (MTw) and of MTw averaged over the four clusters identified by AHC led to distinguish significantly different thermal regime in terms of magnitude and amplitudes (Figure 5a,c) in comparison with MTa (Figure 5b,d).

The MTa patterns of each cluster demonstrate a very similar amplitude and magnitude (Figure 5b,d) with annual amplitude close to 18°C following the same amplitude of thermal regime WarmHighVar. The different response of each thermal regime to same climate conditions suggests other controlling factors than climate determine the annual amplitude and magnitude of Tw .

3.3 | Drivers of thermal sensitivity (TS)

The CART model output leads to develop dichotomic tree plots to better visualize the effects of main drivers (Figure 7). The three most important explanatory variables used by the model to cluster stations as a function of their TS are SF , D (distance from source), and BFI (Figure 6). This is consistent with the RF model output where D , SF , and BFI are identified as the main environmental variables to explain the TS of streams (variable importance $>15\%$; Figure 6). The variables Q_{Aug} and S are also used to differentiate clusters in the CART model and obtained a moderate importance close to 8% with RF. Elevation (E) is identified as the fourth relevant variable with RF model (variable importance = 11%; Figure 6) but is not used by the CART model for

TABLE 1 Metrics averaged for each thermal regime determined with the agglomerative hierarchical clustering

Cluster		TS	b	ΔT_{Jan}	ΔT_{Aug}
WarmHighVar—warm and high variability 47 sites—37%	Max	1.2	3.5	−0.4	1.1
	Med	0.9	2.2	−1.4	−1.6
	Min	0.8	0.6	−2.7	−4.2
WarmLowVar—warm and low variability 23 sites—18%	Max	0.8	4.7	−1.7	1.0
	Med	0.8	3.5	−3.1	−0.3
	Min	0.7	2.5	−4.0	−1.1
ColdHighVar—cold and high variability 44 sites—35%	Max	0.8	4.3	−0.8	5.8
	Med	0.7	2.9	−1.8	1.9
	Min	0.6	1.2	−4.1	0.7
ColdLowVar—cold and low variability 13 sites—10%	Max	0.7	7.6	−2.9	4.7
	Med	0.5	5.7	−4.0	3.5
	Min	0.4	4.9	−5.7	1.1

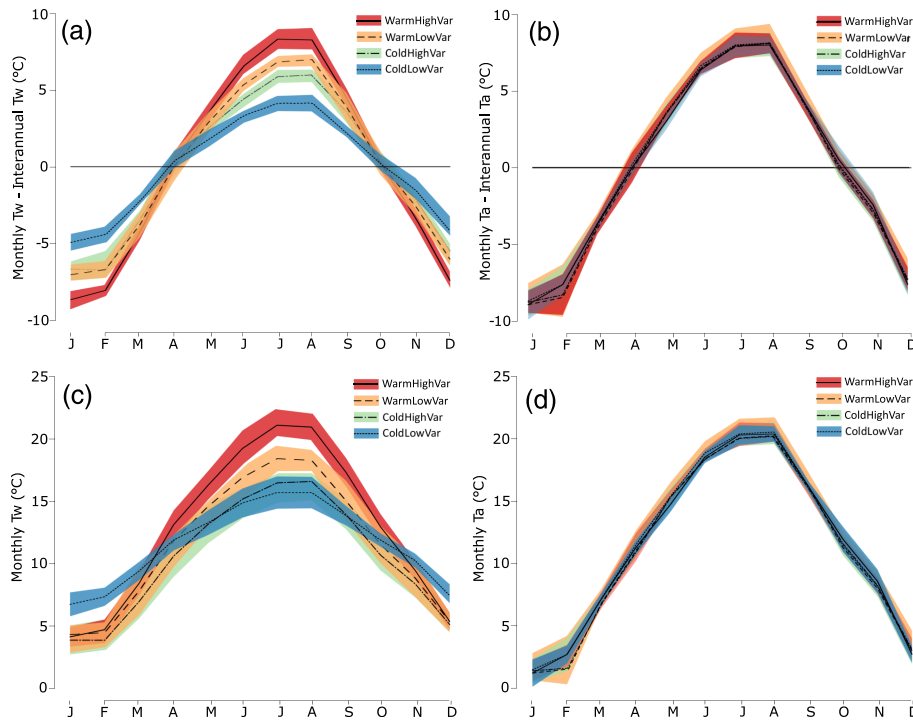


FIGURE 5 Representation of (a) the deviation from the mean annual T_w , (b) the deviation from the mean annual T_a , (c) the monthly T_w , and (d) the monthly T_a averaged over the four thermal regimes identified by agglomerative hierarchical clustering. The colour area bars represent \pm standard deviation of each series

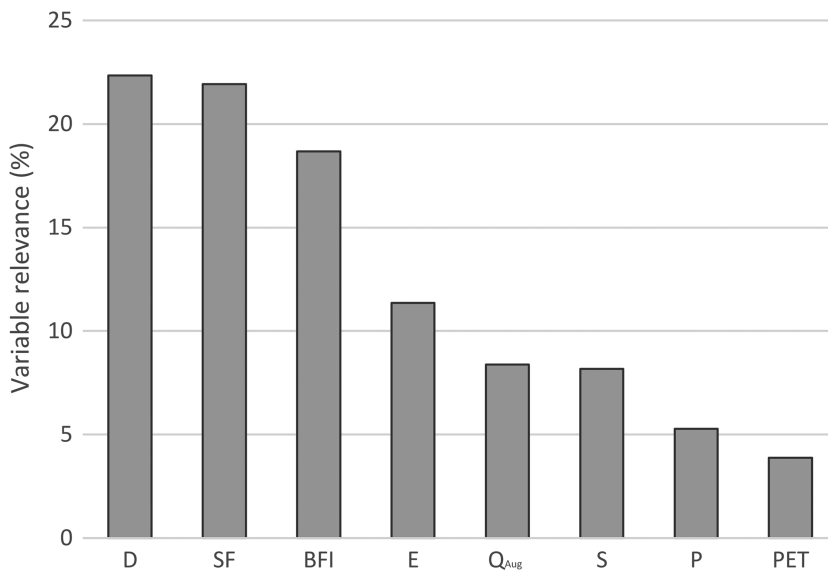


FIGURE 6 Variable importance to explain TS for all stations ranking from the highest to the lowest obtained from random forest

stations clustering. Others variables have a lower influence on TS and are not used in the dichotomic tree plot from the CART model.

- C1—low TS with high SF and high BFI : The combined effect of a high SF ($SF > 30\%$) and a high BFI ($BFI > 0.8$) led to strongly reduce TS of streams (mean TS of 0.5; Figure 7). The 11 stations having these characteristics belong to the thermal regime ColdLowVar (Table 2).
- C2 and C3—low and moderate TS with high SF : Streams with an SF higher than 30% and a BFI less than 0.8 belong mostly to the thermal regime ColdHighVar from AHC results (Figure 7). Q_{Aug} has also an important influence, and we can see contrasts in terms of TS

within this class. The TS was lower for the 17 stations located on streams with a Q_{Aug} value higher than $5 \text{ L s}^{-1} \text{ km}^{-2}$ (mean $TS = 0.67$; C2) than for the 29 remaining stations in C3 with a Q_{Aug} value less than $5 \text{ L s}^{-1} \text{ km}^{-2}$ (mean $TS = 0.76$).

- C4—moderate TS with low SF , low D , and high BFI : The six stations with SF less than 30%, a D less than 120 km, and a BFI greater than 0.8 have a moderate TS (mean TS of 0.71, C4) and belong to the two thermal regimes WarmLowVar and ColdLowVar (Table 2).
- C5 and C6—moderate and high TS with low SF , low D , and low BFI : Stations located on small and medium streams ($S < 120 \text{ km}$) with a BFI lower than 0.8 obtained moderate and high TS . The TS of the 13 stations located on streams with a higher slope ($S > 2.5 \text{ m km}^{-1}$)

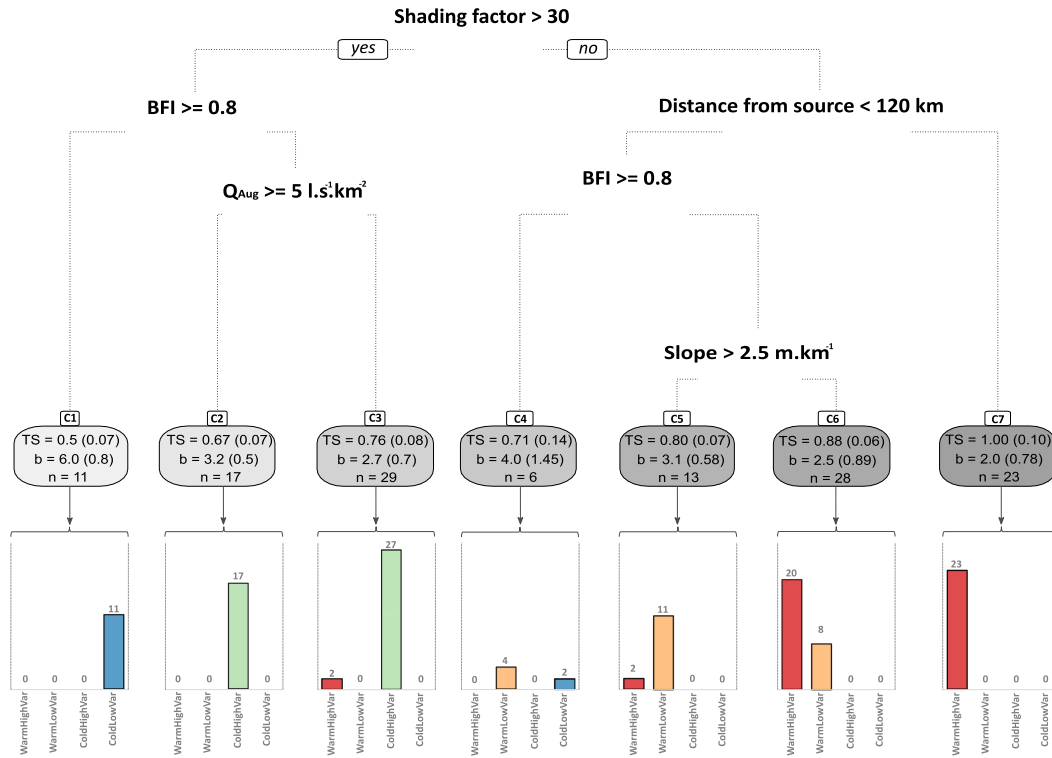


FIGURE 7 Regression and classification on tree developed for TS for all explanatory variables. In each cluster, the mean TS , the mean b , their standard deviation on (in brackets), and the number of stations (n) are presented. Histograms under each branch indicate the thermal regimes of stations identified by the agglomerative hierarchical clustering analysis

TABLE 2 Explanatory variables presented for each thermal regime identify with the agglomerative hierarchical clustering

Cluster		OS	D (km)	E (m)	S (m km ⁻¹)	SF (%)	BFI (—)	Q _{Aug} (L s ⁻¹ km ⁻²)	P (mm)	PET (mm)
WarmHighVar	Max	8	896	323	12.6	60	0.81	1.1	294.0	308.7
	Med	5	122	101	0.5	20	0.72	2	211.2	283.1
	Min	3	19	10	0.1	0	0.51	0.3	144.5	258.6
WarmLowVar	Max	5	145	1120	29.7	29	0.95	3.7	352.2	313.1
	Med	4	36	282	3.3	15	0.74	3	214.0	284.9
	Min	2	7	88	0.1	0	0.64	0.2	140.9	261.0
ColdHighVar	Max	6	96	755	26.1	77	0.78	9.9	302.9	313.5
	Med	4	26	232	3.3	50	0.71	4	231.3	281.8
	Min	2	4	41	0.1	30	0.49	0.1	151.4	256.4
ColdLowVar	Max	5	73	231	3.8	71	0.92	1.7	237.1	312.6
	Med	3	24	122	1.5	50	0.86	5	188.0	283.2
	Min	2	6	65	0.1	19	0.81	0.5	148.0	248.6

have a lower sensitivity (mean TS of 0.81; C5) in comparison with the 28 remaining stations from C6 (mean TS of 0.88; C6). The 13 stations in C5 mostly belong to the thermal regime WarmLowVar, whereas the 28 stations in C6 mostly belong to the thermal regime WarmHighVar (Table 2).

- C7—high TS with low SF , low D , and high BFI : Stations located on streams with low SF ($SF < 30\%$) and a high D ($D > 120 \text{ km}$) have the highest TS (mean TS of 1; C7; Figure 7). The 23 stations having these characteristics belong to the thermal regime WarmHighVar (Table 2).

4 | DISCUSSION

4.1 | Regression robustness and comparison with other studies

In our case study, best correlations between T_a and T_w were obtained with linear regression models and at the weekly time step, with a mean R^2 of 0.96 (standard deviation [SD] = 0.02) determined for the 127 stations. Weekly T_a – T_w linear regressions slightly outperform daily T_a – T_w linear regressions (mean R^2 = 0.88; SD = 0.03) as well as

daily (mean $R^2 = 0.86$; $SD = 0.05$) and weekly (mean $R^2 = 0.93$; $SD = 0.03$) logistic regressions. The weekly time step is more accurate because this time step filters out the lag time between T_a and T_w peaks, which can be of several days. In contrast to other studies (e.g., Kelleher et al., 2012), taking into account a non-linear relationship between T_a and T_w did not improve the performance of the regressions. This is probably explained by the fact that the Loire basin is not subject to T_a (min weekly T_a across the Loire basin between 2008 and 2012 = -8°C) as low as in cold, continental regions studied in the contiguous United States (min $T_a = -20^\circ\text{C}$; Omid Mohseni, Stefan, & Erickson, 1998; Kelleher et al., 2012), which makes T_a – T_w relationship more non-linear for low values. In comparison with the studies using weekly T_a – T_w linear regressions, the R^2 values calculated on the 127 stations are on average higher (mean $R^2 = 0.96$) and comparable with the results of Webb (1992) and O'Driscoll and DeWalle (2006). The negative correlation between TS and b is also consistent with previous studies. Streams controlled by groundwater inflows are characterized by intercepts closer to the regional groundwater temperature and low slopes. Inversely, streams more sensitive to climate conditions have steeper slopes and lower intercepts closest to T_a .

Our TS and b range were consistent with other studies results for linear regression models using a weekly time scale (Table 3). These TS and b values were close to those found by Webb (1992), Stefan and Preud'homme (1993), and Morrill et al. (2005) except that we observe no negative b and the range of our TS and b is slightly higher (Figure 8). This can be explained by a higher number of streams used in our study and by the larger size of the watershed compared with other studies (Table 3). O'Driscoll and DeWalle (2006), Kelleher et al. (2012), and Krider et al. (2013) obtained lower values of TS and higher b values for their studied streams located in karst basins.

4.2 | Groundwater influence on TS

In theory, groundwater influence is more visible on smaller streams because the volume of water is small and the travel time of the water from the source is short and not sufficient to equilibrate T_w with the atmosphere (Beaufort et al., 2016; Mohseni & Stefan, 1999). Groundwater inflow is a heat source during winter and a heat sink during summer resulting in little seasonal variation in T_w and a low TS (Hannah, Malcolm, Soulsby, & Youngson, 2004; Kelleher et al., 2012). Stations with a thermal regime ColdLowVar have low TS (median $TS = 0.5$) and a high intercept (median $b = 5.7^\circ\text{C}$). In other studies, low TS could be due to the upstream influence of reservoirs or impoundments (Erickson & Stefan, 2000; Morrill et al., 2005) or to high groundwater contribution (Kelleher et al., 2012). The 13 stations from the thermal regime ColdLowVar have a reduced annual variation of T_w (blue area; Figure 5a), and their low TS could be reasonably related to the groundwater inflows that decrease T_w response to changes in T_a and increase the thermal inertia of streams (O'Driscoll & DeWalle, 2004). This statement is reinforced by their location on small streams above the main aquifer formations (Figure 4).

CART model results showed that all stations of the thermal regime ColdLowVar have BFI greater than 0.8, which seems to confirm

TABLE 3 TS , b , and R^2 values found in reviewed publications for linear regression models of weekly T_a – T_w relationship

Study	Location	TS slope	b intercept	R^2	Length of record	Köppen–Geiger climate designation
Webb (1992)	36 streams in the United Kingdom	0.65 to 1.16 (1.00)	–0.3 to 3.7 (1.0)	0.86 to 0.97 (0.91)		Cfb
Stefan and Preud'homme (1993)	11 rivers located in the Mississippi River (USA), 150,000 km ²	0.67 to 1.02 (0.86)	0.4 to 5.4 (2.9)	0.75 to 0.97 (0.89)	1 to 8 years	Cfa/Dfa
Pilgrim, Fang, and Stefan (1998)	39 streams in Minnesota (USA)	0.71 to 1.15 (0.99)	–1.5 to 4.8 (1.7)	0.67 to 0.96 (0.85)	1 to 32 years	Dfa/Dfb
Morrill, Bales, and Conklin (2005)	43 U.S. and international streams, 50,000 km ²	0.35 to 1.09 (–)	0.46 to 5.80 (–)	0.42 to 0.83 (–)	1 to 6 years	Cfa/Cfb/Dfa/Dfb
O'Driscoll and DeWalle (2006)	12 streams in Pennsylvania (USA), 450 km ²	0.18 to 0.67 (0.47)	3.2 to 9.1 (6.1)	0.86 to 0.97	3 years	Dfa/Dfb/Cfa
Kelleher et al. (2012)	57 streams in Pennsylvania (USA), 17,500 km ²	0.01 to 1.05 (–)	–	0.09 to 0.98 (–)	2 years or greater	Dfa/Dfb/Cfa
Chang and Psaris (2013)	74 streams in Columbia River basin (USA)	0.10 to 0.81	–	>0.7	–	Csb/Dsb/BWk/Cfb/Dfb
Krider, Magner, Perry, Vondracek, and Ferrington (2013)	40 streams in Minnesota (USA), 7,200 km ²	0.18 to 0.74 (0.3)	2.9 to 8.3 (6.65)	0.59 to 0.98 (0.89)	1 to 4 years	Dfa/Dfb
Present study	127 streams in the Loire basin, 110,000 km ²	0.42 to 1.19 (0.79)	0.6 to 7.5 (3.0)	0.83 to 0.98 (0.95)	1 to 4 years	Cfb

Note. The value in brackets corresponds to the average value.

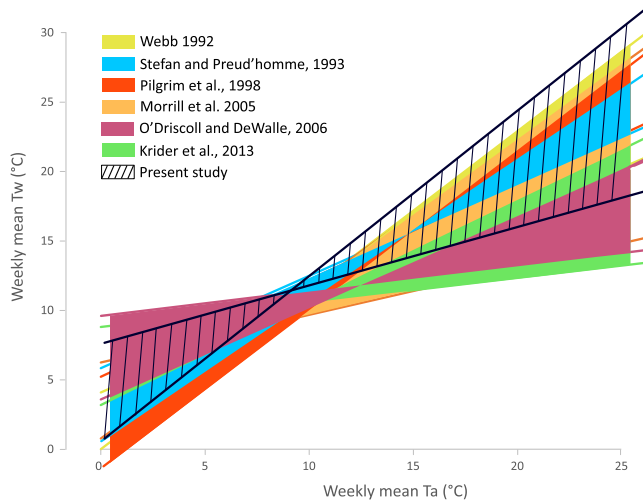


FIGURE 8 Representation of the range of TS and b found in reviewed publications for linear regression models of weekly T_a – T_w relationship

groundwater influences (C1 and C4; Figure 7). The decrease of TS is accentuated when a high BFI is combined with an SF higher than 30% as on the 11 stations in C1 (mean $TS = 0.5$). The shading of riparian vegetation leads to increase the thermal moderation of surface water in summer by shading from solar radiation. The BFI appears as a very influential variable in TS (Figure 6). However, in the Loire basin, TS remains greater than 0.4 even when the BFI is higher than 0.8 and when b is higher than 6°C . In other studies, TS values are close to 0 when the BFI is close to 1 (Kelleher et al., 2012). It could be suspected that the temperature of groundwater inflows feeding streams follows a seasonal trend correlated with T_a and more marked than those observed in the literature (Kelleher et al., 2012; Krider et al., 2013; O'Driscoll & DeWalle, 2006). This could also explain the high residuals of slope intercept regression for stations having a TS lower than 0.6 (Figure 3a).

The variable Q_{Aug} is the mean specific discharge during the warmest month and represents the sustainability of low flows. It is a moderately influential variable in TS (Figure 6). It can be assumed that a stream with a high Q_{Aug} , in the case of natural flowing, benefits from groundwater inflows and/or of important contribution of its tributaries allowing it to maintain a sufficient depth to moderate T_w in summer. CART analysis results showed that streams with a Q_{Aug} value higher than $5 \text{ L s}^{-1} \text{ km}^{-2}$, associated to an SF less than 30% and a BFI less than 0.8, have a lower TS than others stations (C2 vs. C3; Figure 7), which seems to confirm our assumption. However, the importance of Q_{Aug} remains applies to a subset of stations and the BFI remains the main variable representing the influence of groundwater inflows in our dataset.

4.3 | Riparian shading influence on TS

Shortwave (solar) radiation is one of the most influential factors that influence stream temperature and is related directly to the amount of shading provided by riparian vegetation (O'Driscoll & DeWalle, 2006;

Sinokrot & Stefan, 1993). The riparian vegetation captures solar radiation and leads to reduced T_w resulting in a decrease of TS . This effect is particularly visible in summer when the solar radiation is the strongest and represents the main source of energy inputs (e.g., Hannah, Malcolm, Soulsby, & Youngson, 2008). In addition, the riparian vegetation of the Loire basin is mainly composed of deciduous trees, which considerably limit the effect of shading in winter. The influence of the riparian vegetation shading on TS was highlighted by several studies (Chang & Psaris, 2013; Dugdale et al., 2018; Garner, Malcolm, et al., 2017; Hrachowitz et al., 2010; F.L. Jackson et al., 2017; Loicq et al., 2018). However, it is still complex to characterize the own effect of riparian shading, and shading effect is regularly lumped to other drivers of TS moderation (Kelleher et al., 2012; O'Driscoll & DeWalle, 2006).

In our study, we tried to differentiate the effects of shading and of groundwater inflows. The only study of TS and b does not allow to clearly make this distinction because the effect of riparian vegetation shading could be mixed with the effect of groundwater inflows. The ΔT_{Jan} and ΔT_{Aug} were introduced in the AHC model to help make this distinction. Stations in thermal regime WarmHighVar have a high TS ($TS > 0.8$) combined to a small intercept ($b < 3.5^\circ\text{C}$) and are supposed the most influenced by climate and T_a . Their amplitude and magnitude of MT_a and MT_w are very similar and follow the same trend (amplitude of 18°C ; Figure 5a) and do not seem to be moderated by any drivers. Stations in thermal regime ColdHighVar have a lower TS ($TS < 0.8$) and slightly higher intercept (median $b = 2.9^\circ\text{C}$) than in thermal regime WarmHighVar (Table 1). Between thermal regimes ColdHighVar and WarmHighVar, their ΔT_{Jan} is similar ($\Delta T_{Jan} = -1.6^\circ\text{C}$), but T_w is clearly lower than T_a during August for stations in thermal regime ColdHighVar (median $\Delta T_{Aug} = 1.9$). The influence of the riparian vegetation shading is suspected. CART model results seems to confirm this assumption because all stations in ColdHighVar were identified with an SF higher than 30% (C2 and C4; Figure 7). The effects of shading could be accentuated when the specific discharge in August is higher than $5 \text{ L s}^{-1} \text{ km}^{-2}$ (C2; $TS \approx 0.67$) because the thermal inertia of the streams is increased.

4.4 | Landscape factors influence

The distance from the source (D) is a key driver of TS (Figure 6). CART model results showed that stations with a D higher than 120 km obtained the highest TS ($TS = 1$; C7; Figure 7). D is highly positively correlated with the drainage area, and several studies identified this driver as playing an important role in the TS of rivers (Chang & Psaris, 2013; Garner et al., 2014; Hrachowitz et al., 2010; Imholt et al., 2013). Some others studies have also identified the Strahler order, which is correlated to D ($R^2 = 0.6$), as a strong influence factor of TS (Chang & Psaris, 2013; Duchame, 2008; Kelleher et al., 2012; Wehrly, Wiley, & Seelbach, 1998). Streams with a high D and a large drainage area are weakly dependent on upstream conditions, and the travel time of the water body between upstream and downstream allows T_w to equilibrate with T_a (Mohseni & Stefan, 1999), leading to increase TS . Also, a longer D and a larger

catchment area corresponds to lower topographical slopes, slower flow velocities, and greater regional residence time, which allow more time for T_w to adjust to local T_a (Mayer, 2012).

Stations located on small and medium streams, not influenced by shading and groundwater inflows ($SF < 30\%$; $BFI < 0.8$; and $D < 120$ km) belonging to cluster C5 and C6 (Figure 7), obtained a TS less than those of large rivers in C7. There is an influence of S because stations located on streams with a high slope ($S < 2.5$ m km⁻¹) had a mean TS of 0.8 (C5; Figure 7), whereas others had a mean TS of 0.88 (Cluster C6; Figure 7). The stream slope is mostly linked to elevation ($R^2 = 0.65$). A higher slope increases the flow velocity, and the elevation influences T_w over the adiabatic lapse rates of T_a (Hrachowitz et al., 2010) and also through snow and glacier meltwater inflow (Arora, Toffolon, Tockner, & Venohr, 2018; Morrill et al., 2005), which may contribute to decrease TS . P and PET are not relevant in CART model, which may be explained by the relative climatic homogeneity of the study area (Cfb = temperate oceanic climate, Table 3).

4.5 | Implication for river management and river restoration

The study of streams TS makes it possible to identify the most sensitive streams to environmental change (high TS) and potentially the most sensitive to the effects of climate change. The stationarity of all processes influencing T_w is difficult to estimate because it implies the use of physically based models directly integrating energy fluxes because the only study of TS tends to underestimate the warming of climate change (Leach & Moore, 2019). However, streams studied here have a natural thermal regime and are not influenced by anthropogenic activities. These natural streams sensitive to environmental changes in the present time (high TS) will always be sensitive to environmental changes in the future without human actions. The goal of our approach is to identify the most climate-sensitive streams, linking them to environmental or hydrological features, to guide stakeholders to pay particular attention to them.

Our analysis identified D , BFI , and SF as the main factors influencing TS in the Loire basin. The major streams of the Loire catchment ($D > 120$ km) show the highest TS value (mean $TS = 1$) and appear highly sensitive to the effects of global warming. For these streams having a large wet width (>50 m), the effects of shading from riparian vegetation are very small, and actions to reduce TS are limited. Thermal anomalies could be detected by aerial infrared survey (Wawrzyniak, Piégay, & Poirol, 2012) and be preserved by limiting advective thermal mixing (Kurylyk et al., 2015) or activated by geomorphological restoration of streams (Eschbach et al., 2017; Loheide & Gorelick, 2006). On small and medium streams, it is necessary to preserve and/or favour the presence of riparian vegetation to moderate TS (Fabris, Malcolm, Buddendorf, & Soulsby, 2018). The effects will be most pronounced, in comparison with large streams, because of their smaller width, but investments have to be made strategically (Isaak et al., 2017; Johnson & Wilby, 2015). From a watershed management perspective, stream shading would be less effective in streams where T_w is already strongly moderated by groundwater inflows but more

effective along losing reaches or stream reaches distant from groundwater inflows (O'Driscoll & DeWalle, 2006).

Streams with a low TS have a limited surface water heating during summer and may provide thermal refuges for thermo-sensitive aquatic species (macroinvertebrates, stream-dwelling amphibians, and fish species; Isaak et al., 2017). In order to limit these warmings and preserve ecosystems, it seems important to identify streams constituting cold-water thermal refuges (with low TS) and to restore and preserve thermal diversity in the hydrographical network (Torgersen, Ebersole, & Keenan, 2012). However, the main factors limiting TS (BFI and SF) could change in the future, and several streams could become much more sensitive to environmental change (Leach & Moore, 2019). For example, the loss in groundwater inflows would result in greater meteorological controls increasing the annual amplitude of T_w (O'Driscoll & DeWalle, 2006). Limiting water abstraction during low-flow periods may avoid a disconnection of groundwater/surface water exchanges and ensure environmental flows during the summer (Elmore, Null, & Mouzon, 2016). Some cooling strategies proposed to reconnect streams to floodplains and to facilitate greater lateral and hyporheic flow exchanges (Beechie et al., 2012; Daniel Caissie & Luce, 2017; Kurylyk et al., 2015) but need to be tested at a regional scale. To apply efficient and effective actions, river managers have to focus on small and medium streams and can use the environmental variables identified in our classification results as indicators to assess the climate sensitivity of unmonitored streams.

5 | CONCLUSION

In this study, we proposed a framework to compare thermal sensitivity (TS) for 127 stations located on temperate streams between 2008 and 2012 and to cluster stations sharing similar natural thermal regimes, not influence by anthropogenic effects. On the basis of weekly T_a - T_w relationships, four thermal regimes were identified with differing annual T_w in terms of magnitude and amplitudes in comparison with T_a . We linked each cluster to different environmental controlling factors as inferred by TS . This highlighted that shading from riparian vegetation, groundwater inflows, and the distance from the source of streams were the main drivers of the moderation of streams located in the Loire catchment. Streams influenced by both groundwater inflows and shading are the most moderated with the lowest TS and an annual amplitude of T_w around half the annual amplitude of T_a . Inversely, stations located on large streams or on streams slightly or not influenced by groundwater inflows and/or shading showed the highest TS and are very climate sensitive. Their T_w amplitude and magnitude were very close to those of T_a ; consequently, these rivers are deemed the most sensitive to the effects of future climate change.

The T_w metrics and the environmental variables remain simple to determine and can easily be applied in others catchments at a regional scale. One of the perspectives to this work would be to explore if main controlling factors of the T_w variability identified here are the same in different climate and physiographical regions elsewhere. We observe that almost invariability streams studied in reviewed publications for

linear regression models of weekly T_a – T_w relationship (Table 3) correspond to temperate and continental climatic regions. It would be interesting to study streams from different climatic contexts to understand how controls of TS may vary. Furthermore, it would be insightful to explore how TS may be modified by anthropogenic effects (dams, weirs, and other flow augmentation/abstractions, etc.). Management agencies can use our findings on thermal sensitivity for prioritizing restoration areas to moderate stream temperature and undertake mitigation and adaptation actions to protect sensitive aquatic species in the context of a changing environment.

DATA AVAILABILITY STATEMENT

Temperature used in this study are available from the French Biodiversity Agency (AFB; www.afbiodiversite.fr). Restrictions apply to the availability of these data, which were used under license herein. Data are available at <http://www.naiades.eaufrance.fr> with the permission of the French Biodiversity Agency (www.naiades.eaufrance.fr/formulaire/contact). Discharge data are available from the French river flow monitoring network (HYDRO database, <http://www.hydro.eaufrance.fr/>). Restrictions apply to the availability of meteorological data, which were used under license herein with the permission of Météo France (www.meteofrance.fr).

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